WHICH HIP MODEL BEST PREDICTS BIOLOGICAL TORQUES ACROSS LOCOMOTION MODES? A SIMULATION STUDY

Po Chuan Chen, Benjamin A. Shafer[1*], Wei-Lin Du, Aaron J. Young, Gregory S. Sawicki
[1]George W. Woodruff School of Mechanical Engineering, Georgia Institute of Technology, Atlanta GA, USA
*Corresponding author's email: ben.shafer@gatech.edu

Introduction: Wearable assistive devices can augment people's mobility but lack a robust control strategy that can adapt to the various locomotion modes (speeds, slopes, and gaits) of everyday life. Human-in-the-loop optimization methods can find effective assistance at each mode, but these methods are time-consuming and exhausting for both the user and experimenter. Knowing that biological torque changes for each mode, we believe an analytical controller that could predict biological torque (BioTorque) across modes without user adjustment would address this issue. We simulated how well three optimized hip exoskeleton control models (impedance control (IMP), proportional myoelectric control (PMC), and muscle activity driven neuromuscular model-based control (NMM)) could mimic BioTorque across 26 different locomotion modes using only joint kinematics (angle and its derivative) and/or muscle activity (gluteus maximus and rectus femoris) as inputs (Fig. 1A). We hypothesized that the NMM would better predict BioTorque than IMP or PMC, as it leverages both kinematics and muscle activity.

Methods: We drove each model and comparison using previously recorded locomotion data from 5 participants including 4 speeds (1.25 m/s, 2 m/s walking, 2 m/s running, and 3.25 m/s running) across 7 slopes (±15° (except at 3.25 m/s running), ±10°, ±5°, and 0°). Each model was driven by the appropriate signals for that mode and the model torque output was compared against the measured, ground-truth BioTorque (Fig. 1C) using mean absolute error (MAE). The model parameters were tuned to minimize the MAE. To ensure we found the best tuning for each model, we compared three optimization algorithms (Surrogate, Bayesian, and CMAES) with enough iterations for each to converge within 5% MAE. We chose Surrogate, as it yielded the lowest error and the fastest convergence rate. IMP model took joint angle as input and then implemented a virtual spring and damper to generate an output torque (Fig. 1B). On the other hand, PMC model took measures EMG as input, amplified it (G_{EMG}) and concatenated it with a delay unit (Fig. 1B). Lastly, EMG-driven NMM-based controller [1] took in both joint angle and EMG as inputs, and implemented a Hill-type muscle-tendon model for each muscle, including a linear tendon spring in series with a contractile element representing muscle force and a non-linear spring in parallel (Fig. 1B). To calculate how well each model could mimic BioTorque at each trained mode, we split the data by gait cycles in a 3:1 training-to-validation ratio and measured the MAE only on the validation data. These results were averaged across participants and then the 26 modes for each model (Fig. 1D left). To determine how each model could predict BioTorque without retraining, we trained the model on one mode, measured MAE on the other 25 modes, and calculated the average per mode. We repeated this for all 26 modes and then averaged MAE across modes for each model (Fig. 1D right).

Results & Discussion: The IMP model best mimicked measured BioTorque, showing the lowest optimization (training) MAE at 0.17 Nm (Fig. 1D left) on average across participants and modes. PMC showed worst performance, with the highest MAE. Furthermore, IMP model, with only 6 tunable parameters, also outperformed the more complex NMM and PMC models in terms of adaptability, with an MAE of 0.25 Nm (Fig. 1D right). It seems incorporating measured gluteus maximus and rectus femoris muscle activity actually hinders BioTorque estimates, possibly due to their high variability and differences in peak timing compared to BioTorque. On the contrary, joint kinematics provide a less variable and more effective signal to drive analytical models.

Significance: IMP model, a simpler architecture with fewer parameters, can better predict BioTorque than more physiologically complex models. Leveraging this understanding will help design exoskeletons controllers focused on motion sensors, with controller based on joint kinematics to provide continuous assistance across modes.

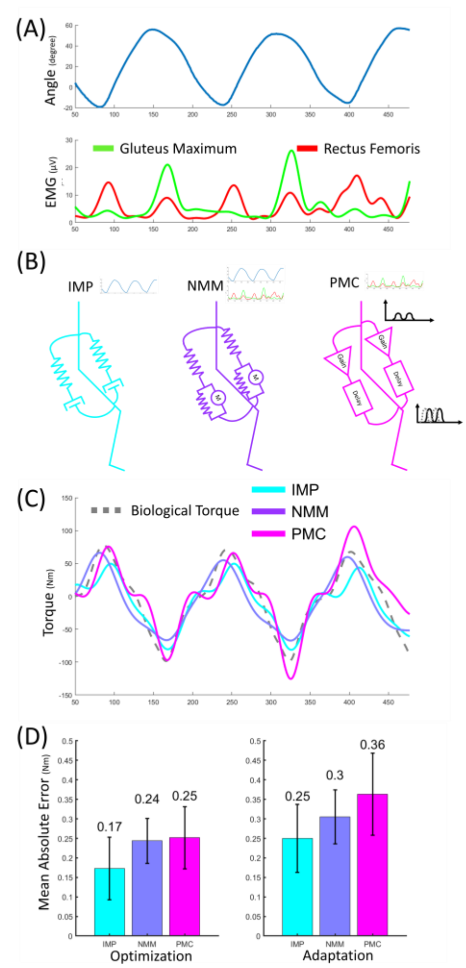

Figure 1: (A) Experimental angle and EMG data for model inputs. (B) Diagram of each model. The number of model parameters are 6 for IMP, 32 for NMM, and 4 for PMC. (C) Comparison between BioTorque and output torques of models. (D) MAE of optimization and adaptation.

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References: [1] Markowitz et al. (2011) Philosophical Transactions